autogluon_each_location

October 17, 2023

[1]:
```python
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*60
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = ["hour", "year", "month", "weekday"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

use_groups = False
n_groups = 8

auto_stack = True
num_stack_levels = None
num_bag_folds = None


use_tune_data = False
use_test_data = False
tune_and_test_length = 24*30*3 # 3 months from end
holdout_frac = None
use_bag_holdout = False # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False
sample_weight_estimated = 1

run_analysis = True
```

[2]:
```python
import pandas as pd
import numpy as np
```

```python
import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
       'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
       'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    X_shifted = X[X.index.minute==0][columns].copy()
    # loop through all rows and check if index + 1 hour is in the index, if so␣
↪get that value, else nan
    count1 = 0
    count2 = 0
    for i in range(len(X_shifted)):
        if X_shifted.index[i] + pd.Timedelta('1 hour') in X.index:
            count1 += 1
            X_shifted.iloc[i] = X.loc[X_shifted.index[i] + pd.Timedelta('1␣
↪hour')][columns]
        else:
            count2 += 1
            X_shifted.iloc[i] = np.nan

    print("COUNT1", count1)
    print("COUNT2", count2)

    X_old_unshifted = X[X.index.minute==0][columns]
    # rename X_old_unshifted columns to have _not_shifted at the end
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.
↪columns]

    # put the shifted columns back into the original dataframe
    #X[columns] = X_shifted[columns]



    date_calc = None
    if "date_calc" in X.columns:
```

```python
        date_calc = X[X.index.minute == 0]['date_calc']

    # resample to hourly
    X = X.resample('H').mean()

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    # add sample weights, which are 1 for observed and 3 for estimated
    X_train_observed["sample_weight"] = 1
    X_train_estimated["sample_weight"] = sample_weight_estimated
    X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)
```

```python
    return X_train_observed, X_train_estimated, X_test, y_train



def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] = X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True, right_index=True)
```

```
    # print number of nans in sample_weight
    print(f"Number of nans in sample_weight: {X_train['sample_weight'].isna().
 ↪sum()}")
    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
COUNT1 4392
COUNT2 2
```

```
COUNT1 702
COUNT2 18
Number of nans in sample_weight: 0
Number of nans in y: 0
Processing location B…
COUNT1 29232
COUNT2 1
COUNT1 4392
COUNT2 2
COUNT1 702
COUNT2 18
Number of nans in sample_weight: 0
Number of nans in y: 4
Processing location C…
COUNT1 29206
COUNT2 1
COUNT1 4392
COUNT2 2
COUNT1 702
COUNT2 18
Number of nans in sample_weight: 0
Number of nans in y: 6059
```

1 Feature enginering

[3]:
```
import numpy as np
import pandas as pd

X_train.dropna(subset=['y'], inplace=True)



for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

print(X_train.head())






if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
 ↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

```

```python
    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
 ↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())




to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
 ↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 22:00:00                     7.700              1.22825
2019-06-02 23:00:00                     7.700              1.22350
2019-06-03 00:00:00                     7.875              1.21975
2019-06-03 01:00:00                     8.425              1.21800
2019-06-03 02:00:00                     8.950              1.21800

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 22:00:00           1728.949951               0.000000
2019-06-02 23:00:00           1689.824951               0.000000
```

```
2019-06-03 00:00:00          1563.224976               0.000000
2019-06-03 01:00:00          1283.425049            6546.899902
2019-06-03 02:00:00          1003.500000          102225.898438

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 22:00:00             0.00       1728.949951              0.0
2019-06-02 23:00:00             0.00       1689.824951              0.0
2019-06-03 00:00:00             0.00       1563.224976              0.0
2019-06-03 01:00:00             0.75       1283.425049              0.0
2019-06-03 02:00:00            23.10       1003.500000              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                    …
2019-06-02 22:00:00      280.299988          0.000          0.000000  …
2019-06-02 23:00:00      280.299988          0.000          0.000000  …
2019-06-03 00:00:00      280.649994          0.000          0.000000  …
2019-06-03 01:00:00      281.674988          0.300       7743.299805  …
2019-06-03 02:00:00      282.500000         11.975      60137.601562  …

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 22:00:00               -0.500                      0.0
2019-06-02 23:00:00                0.275                      0.0
2019-06-03 00:00:00                0.750                      0.0
2019-06-03 01:00:00                0.875                      0.0
2019-06-03 02:00:00                0.925                      0.0

                     sample_weight  is_estimated      y  location  hour  year  \
ds
2019-06-02 22:00:00              1             0   0.00         A    22  2019
2019-06-02 23:00:00              1             0   0.00         A    23  2019
2019-06-03 00:00:00              1             0   0.00         A     0  2019
2019-06-03 01:00:00              1             0   0.00         A     1  2019
2019-06-03 02:00:00              1             0  19.36         A     2  2019

                     month  weekday
ds
2019-06-02 22:00:00      6        6
2019-06-02 23:00:00      6        6
2019-06-03 00:00:00      6        0
2019-06-03 01:00:00      6        0
2019-06-03 02:00:00      6        0

[5 rows x 53 columns]
```

[4]:

```
from autogluon.tabular import TabularDataset, TabularPredictor
from autogluon.timeseries import TimeSeriesDataFrame
import numpy as np
train_data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
train_data['ds'] = pd.to_datetime(train_data['ds'])
train_data = train_data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
train_set = TabularDataset(train_data[train_data["ds"] < split_time])
test_set = TabularDataset(train_data[train_data["ds"] >= split_time])
if use_groups:
    test_set = test_set.drop(columns=['group'])

if do_drop_ds:
    train_set = train_set.drop(columns=['ds'])
    test_set = test_set.drop(columns=['ds'])
    train_data = train_data.drop(columns=['ds'])


def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

tuning_data = None
if use_tune_data:
    train_data = train_set
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            loc_tuning_data = loc_test_set.iloc[:len(loc_test_set)//2]
            loc_test_data = loc_test_set.iloc[len(loc_test_set)//2:]
```

```
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
 ↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
 ↪the tuning data.
    tuning_data = normalize_sample_weights_per_location(tuning_data)


else:
    if use_test_data:
        train_data = train_set
        test_data = test_set
        print("Shape of test", test_data.shape[0])

# ensure sample weights for your training (or tuning) data sum to the number of␣
 ↪rows in the training (or tuning) data.
train_data = normalize_sample_weights_per_location(train_data)
if use_test_data:
    test_data = normalize_sample_weights_per_location(test_data)
```

[5]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_set, label="y",␣
 ↪sample=None)
```

train_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	92951	760			6.017393	
air_density_2m:kgm3	92951	1374			1.255435	
ceiling_height_agl:m	76534	63118			2888.30088	
clear_sky_energy_1h:J	92945	48602			515183.641476	
clear_sky_rad:W	92951	20312			143.098015	
cloud_base_agl:m	86213	63893			1735.995178	
dew_point_2m:K	92951	2006			275.237958	
diffuse_rad:W	92951	11222			39.395201	
diffuse_rad_1h:J	92945	48552			142196.335278	
direct_rad:W	92951	14417			50.24518	
direct_rad_1h:J	92945	41885			180744.819009	
effective_cloud_cover:p	92951	5713			67.08644	

elevation:m	92951	3			11.401739
fresh_snow_1h:cm	92945	39			0.009641
fresh_snow_3h:cm	92945	70			0.029042
fresh_snow_6h:cm	92945	96			0.058143
hour	93023	24			11.501338
is_day:idx	92951	5			0.483303
is_estimated	93023	2			0.118218
is_in_shadow:idx	92951	5			0.564284
location	93023	3	A	34085	
month	93023	12			6.290423
msl_pressure:hPa	92951	3733			1009.502496
precip_5min:mm	92951	271			0.005657
precip_type_5min:idx	92951	15			0.084348
pressure_100m:hPa	92951	3760			995.818828
pressure_50m:hPa	92951	3809			1001.949597
rain_water:kgm2	92951	39			0.009566
relative_humidity_1000hPa:p	92951	3837			73.670589
sample_weight	93023	2			1.0
sfc_pressure:hPa	92951	3817			1008.107684
snow_depth:cm	92951	491			0.193164
snow_melt_10min:mm	92951	66			0.000273
snow_water:kgm2	92951	162			0.090299
sun_azimuth:d	92951	88092			179.648569
sun_elevation:d	92951	76035			-1.206875
super_cooled_liquid_water:kgm2	92951	53			0.056897
t_1000hPa:K	92951	1994			279.430664
total_cloud_cover:p	92951	5608			73.692549
visibility:m	92951	91240			33025.01299
weekday	93023	7			3.002182
wind_speed_10m:ms	92951	596			3.038167
wind_speed_u_10m:ms	92951	999			0.664565
wind_speed_v_10m:ms	92951	850			0.685095
y	93023	12379			287.022737
year	93023	5			2020.694979

	std	min	25%	50%	\
absolute_humidity_2m:gm3	2.711862	0.5	4.025	5.45	
air_density_2m:kgm3	0.036567	1.13925	1.23025	1.255	
ceiling_height_agl:m	2536.68272	27.8	1087.60625	1887.8875	
clear_sky_energy_1h:J	820542.211615	0.0	0.0	4551.0	
clear_sky_rad:W	227.959967	0.0	0.0	1.65	
cloud_base_agl:m	1809.297261	27.5	591.925	1164.525	
dew_point_2m:K	6.829573	247.425	270.75	274.975	
diffuse_rad:W	60.518576	0.0	0.0	0.925	
diffuse_rad_1h:J	215920.02629	0.0	0.0	9952.6	
direct_rad:W	112.91716	0.0	0.0	0.0	
direct_rad_1h:J	401738.480227	0.0	0.0	0.0	
effective_cloud_cover:p	34.269564	0.0	42.0	79.95	

elevation:m	7.877236	6.0	6.0	7.0
fresh_snow_1h:cm	0.112651	0.0	0.0	0.0
fresh_snow_3h:cm	0.280779	0.0	0.0	0.0
fresh_snow_6h:cm	0.481544	0.0	0.0	0.0
hour	6.920154	0.0	6.0	12.0
is_day:idx	0.485974	0.0	0.0	0.25
is_estimated	0.322868	0.0	0.0	0.0
is_in_shadow:idx	0.483166	0.0	0.0	1.0
location				
month	3.58724	1.0	3.0	6.0
msl_pressure:hPa	13.085625	944.375	1001.4	1010.35
precip_5min:mm	0.029169	0.0	0.0	0.0
precip_type_5min:idx	0.330071	0.0	0.0	0.0
pressure_100m:hPa	13.004987	929.975	987.775	996.75
pressure_50m:hPa	13.063835	935.75	993.85	1002.85
rain_water:kgm2	0.041121	0.0	0.0	0.0
relative_humidity_1000hPa:p	14.229107	19.575	64.2	76.0
sample_weight	0.0	1.0	1.0	1.0
sfc_pressure:hPa	13.124815	941.55	999.975	1009.0
snow_depth:cm	1.253925	0.0	0.0	0.0
snow_melt_10min:mm	0.004249	0.0	0.0	0.0
snow_water:kgm2	0.237841	0.0	0.0	0.0
sun_azimuth:d	97.282534	6.983	94.67875	179.97975
sun_elevation:d	23.970707	-49.932	-18.59975	-0.8645
super_cooled_liquid_water:kgm2	0.105794	0.0	0.0	0.0
t_1000hPa:K	6.515625	258.025	274.9	278.65002
total_cloud_cover:p	34.021943	0.0	53.225	93.05
visibility:m	17913.98226	132.375	16862.7995	36846.176
weekday	2.000947	0.0	1.0	3.0
wind_speed_10m:ms	1.760291	0.025	1.675	2.7
wind_speed_u_10m:ms	2.802007	-7.225	-1.35	0.3
wind_speed_v_10m:ms	1.878808	-8.4	-0.575	0.725
y	766.411327	-0.0	0.0	0.0
year	1.187146	2019.0	2020.0	2021.0

	75%	max	dtypes	missing_count	\
absolute_humidity_2m:gm3	7.825	17.35	float64	72	
air_density_2m:kgm3	1.2785	1.441	float64	72	
ceiling_height_agl:m	3988.4125	12294.901	float64	16489	
clear_sky_energy_1h:J	778482.3	3006697.2	float64	78	
clear_sky_rad:W	216.8	835.65	float64	72	
cloud_base_agl:m	2079.25	11673.725	float64	6810	
dew_point_2m:K	280.5	293.625	float64	72	
diffuse_rad:W	65.275	334.75	float64	72	
diffuse_rad_1h:J	236534.8	1182265.4	float64	78	
direct_rad:W	29.3	683.4	float64	72	
direct_rad_1h:J	113395.3	2445897.0	float64	78	
effective_cloud_cover:p	98.637497	100.0	float64	72	

elevation:m	24.0	24.0	float64	72
fresh_snow_1h:cm	0.0	7.1	float64	78
fresh_snow_3h:cm	0.0	20.6	float64	78
fresh_snow_6h:cm	0.0	34.0	float64	78
hour	17.0	23.0	int64	
is_day:idx	1.0	1.0	float64	72
is_estimated	0.0	1.0	int64	
is_in_shadow:idx	1.0	1.0	float64	72
location			object	
month	10.0	12.0	int64	
msl_pressure:hPa	1018.55	1044.1	float64	72
precip_5min:mm	0.0	0.6225	float64	72
precip_type_5min:idx	0.0	5.0	float64	72
pressure_100m:hPa	1004.925	1030.875	float64	72
pressure_50m:hPa	1011.05	1037.25	float64	72
rain_water:kgm2	0.0	1.1	float64	72
relative_humidity_1000hPa:p	85.05	100.0	float64	72
sample_weight	1.0	1.0	float64	
sfc_pressure:hPa	1017.2	1043.725	float64	72
snow_depth:cm	0.0	18.2	float64	72
snow_melt_10min:mm	0.0	0.18	float64	72
snow_water:kgm2	0.1	5.65	float64	72
sun_azimuth:d	264.41998	348.48752	float64	72
sun_elevation:d	15.25075	49.94375	float64	72
super_cooled_liquid_water:kgm2	0.1	1.375	float64	72
t_1000hPa:K	283.95	303.25	float64	72
total_cloud_cover:p	99.9	100.0	float64	72
visibility:m	48308.9875	75489.33	float64	72
weekday	5.0	6.0	int64	
wind_speed_10m:ms	4.05	13.275	float64	72
wind_speed_u_10m:ms	2.5	11.2	float64	72
wind_speed_v_10m:ms	1.875	8.825	float64	72
y	172.92	5733.42	float64	
year	2022.0	2023.0	int64	

	missing_ratio	raw_type	variable_type	\
absolute_humidity_2m:gm3	0.000774	float	numeric	
air_density_2m:kgm3	0.000774	float	numeric	
ceiling_height_agl:m	0.177257	float	numeric	
clear_sky_energy_1h:J	0.000839	float	numeric	
clear_sky_rad:W	0.000774	float	numeric	
cloud_base_agl:m	0.073208	float	numeric	
dew_point_2m:K	0.000774	float	numeric	
diffuse_rad:W	0.000774	float	numeric	
diffuse_rad_1h:J	0.000839	float	numeric	
direct_rad:W	0.000774	float	numeric	
direct_rad_1h:J	0.000839	float	numeric	
effective_cloud_cover:p	0.000774	float	numeric	

elevation:m	0.000774	float	category
fresh_snow_1h:cm	0.000839	float	numeric
fresh_snow_3h:cm	0.000839	float	numeric
fresh_snow_6h:cm	0.000839	float	numeric
hour		int	numeric
is_day:idx	0.000774	float	category
is_estimated		int	category
is_in_shadow:idx	0.000774	float	category
location		object	category
month		int	category
msl_pressure:hPa	0.000774	float	numeric
precip_5min:mm	0.000774	float	numeric
precip_type_5min:idx	0.000774	float	category
pressure_100m:hPa	0.000774	float	numeric
pressure_50m:hPa	0.000774	float	numeric
rain_water:kgm2	0.000774	float	numeric
relative_humidity_1000hPa:p	0.000774	float	numeric
sample_weight		float	category
sfc_pressure:hPa	0.000774	float	numeric
snow_depth:cm	0.000774	float	numeric
snow_melt_10min:mm	0.000774	float	numeric
snow_water:kgm2	0.000774	float	numeric
sun_azimuth:d	0.000774	float	numeric
sun_elevation:d	0.000774	float	numeric
super_cooled_liquid_water:kgm2	0.000774	float	numeric
t_1000hPa:K	0.000774	float	numeric
total_cloud_cover:p	0.000774	float	numeric
visibility:m	0.000774	float	numeric
weekday		int	category
wind_speed_10m:ms	0.000774	float	numeric
wind_speed_u_10m:ms	0.000774	float	numeric
wind_speed_v_10m:ms	0.000774	float	numeric
y		float	numeric
year		int	category

	special_types
absolute_humidity_2m:gm3	
air_density_2m:kgm3	
ceiling_height_agl:m	
clear_sky_energy_1h:J	
clear_sky_rad:W	
cloud_base_agl:m	
dew_point_2m:K	
diffuse_rad:W	
diffuse_rad_1h:J	
direct_rad:W	
direct_rad_1h:J	
effective_cloud_cover:p	

```
elevation:m
fresh_snow_1h:cm
fresh_snow_3h:cm
fresh_snow_6h:cm
hour
is_day:idx
is_estimated
is_in_shadow:idx
location
month
msl_pressure:hPa
precip_5min:mm
precip_type_5min:idx
pressure_100m:hPa
pressure_50m:hPa
rain_water:kgm2
relative_humidity_1000hPa:p
sample_weight
sfc_pressure:hPa
snow_depth:cm
snow_melt_10min:mm
snow_water:kgm2
sun_azimuth:d
sun_elevation:d
super_cooled_liquid_water:kgm2
t_1000hPa:K
total_cloud_cover:p
visibility:m
weekday
wind_speed_10m:ms
wind_speed_u_10m:ms
wind_speed_v_10m:ms
y
year
```

test_data dataset summary

```
                              count  unique top  freq            mean  \
absolute_humidity_2m:gm3       5791     289                  4.192639
air_density_2m:kgm3            5791     640                  1.280018
ceiling_height_agl:m           4395    4247               3278.267059
clear_sky_energy_1h:J          5788    3059             469132.824948
clear_sky_rad:W                5791    2046                130.246477
cloud_base_agl:m               4934    4719               1733.271034
dew_point_2m:K                 5791     948                270.733081
diffuse_rad:W                  5791    2237                 42.175259
diffuse_rad_1h:J               5788    3065             152461.828645
direct_rad:W                   5791    1829                 51.829421
direct_rad_1h:J                5788    2676             186526.762509
```

effective_cloud_cover:p	5791	2100			66.598541
elevation:m	5791	3			11.262131
fresh_snow_1h:cm	5788	23			0.032308
fresh_snow_3h:cm	5788	42			0.100259
fresh_snow_6h:cm	5788	60			0.204492
hour	5791	24			11.499396
is_day:idx	5791	5			0.488387
is_estimated	5791	1			1.0
is_in_shadow:idx	5791	5			0.555085
location	5791	3	A	2161	
month	5791	4			3.045761
msl_pressure:hPa	5791	2040			1012.678587
precip_5min:mm	5791	63			0.003687
precip_type_5min:idx	5791	12			0.086039
pressure_100m:hPa	5791	2124			998.781639
pressure_50m:hPa	5791	2134			1005.02648
rain_water:kgm2	5791	7			0.000984
relative_humidity_1000hPa:p	5791	2051			70.810205
sample_weight	5791	1			1.0
sfc_pressure:hPa	5791	2148			1011.29959
snow_depth:cm	5791	78			0.131661
snow_melt_10min:mm	5791	38			0.000695
snow_water:kgm2	5791	68			0.078393
sun_azimuth:d	5791	5681			179.475343
sun_elevation:d	5791	5093			-0.927197
super_cooled_liquid_water:kgm2	5791	31			0.035175
t_1000hPa:K	5791	825			275.185991
total_cloud_cover:p	5791	1838			71.785616
visibility:m	5791	5784			29884.461577
weekday	5791	7			3.018304
wind_speed_10m:ms	5791	424			3.227599
wind_speed_u_10m:ms	5791	672			0.668019
wind_speed_v_10m:ms	5791	483			0.538344
y	5791	2304			272.991992
year	5791	1			2023.0

	std	min	25%	\
absolute_humidity_2m:gm3	1.300644	1.1	3.35	
air_density_2m:kgm3	0.024372	1.219	1.26375	
ceiling_height_agl:m	2590.751931	27.925	1149.0625	
clear_sky_energy_1h:J	689638.596662	0.0	0.0	
clear_sky_rad:W	191.578221	0.0	0.0	
cloud_base_agl:m	1987.046511	27.5	525.4375	
dew_point_2m:K	4.634046	255.05	268.33749	
diffuse_rad:W	59.158733	0.0	0.0	
diffuse_rad_1h:J	211011.771342	0.0	0.0	
direct_rad:W	110.450287	0.0	0.0	
direct_rad_1h:J	393513.65175	0.0	0.0	

effective_cloud_cover:p	37.583548	0.0	33.6375
elevation:m	7.8114	6.0	6.0
fresh_snow_1h:cm	0.170919	0.0	0.0
fresh_snow_3h:cm	0.425766	0.0	0.0
fresh_snow_6h:cm	0.738932	0.0	0.0
hour	6.920293	0.0	6.0
is_day:idx	0.486436	0.0	0.0
is_estimated	0.0	1.0	1.0
is_in_shadow:idx	0.483636	0.0	0.0
location			
month	0.850975	1.0	2.0
msl_pressure:hPa	13.953847	975.3	1003.875
precip_5min:mm	0.017701	0.0	0.0
precip_type_5min:idx	0.393918	0.0	0.0
pressure_100m:hPa	13.825369	962.4	989.9
pressure_50m:hPa	13.873049	968.45	996.087475
rain_water:kgm2	0.009596	0.0	0.0
relative_humidity_1000hPa:p	14.940249	21.325	60.75
sample_weight	0.0	1.0	1.0
sfc_pressure:hPa	13.921629	974.55	1002.25
snow_depth:cm	0.635847	0.0	0.0
snow_melt_10min:mm	0.007333	0.0	0.0
snow_water:kgm2	0.189057	0.0	0.0
sun_azimuth:d	96.891969	14.913	94.264625
sun_elevation:d	20.775858	-44.28175	-17.109625
super_cooled_liquid_water:kgm2	0.084895	0.0	0.0
t_1000hPa:K	3.823552	261.975	272.8
total_cloud_cover:p	37.578218	0.0	41.8
visibility:m	14669.627165	1215.4	18727.05
weekday	1.989873	0.0	1.0
wind_speed_10m:ms	1.869023	0.05	1.725
wind_speed_u_10m:ms	3.12501	-7.15	-1.75
wind_speed_v_10m:ms	1.838513	-5.3	-0.8
y	770.841016	-0.0	0.0
year	0.0	2023.0	2023.0

	50%	75%	max	dtypes \
absolute_humidity_2m:gm3	4.3	5.05	7.7	float64
air_density_2m:kgm3	1.279	1.29375	1.37175	float64
ceiling_height_agl:m	2618.95	4661.025	12294.901	float64
clear_sky_energy_1h:J	11008.5	791394.0	2554290.5	float64
clear_sky_rad:W	2.675	221.925	710.5	float64
cloud_base_agl:m	904.825	2014.962525	10674.3	float64
dew_point_2m:K	271.6	273.9	280.4	float64
diffuse_rad:W	1.775	78.4875	311.95	float64
diffuse_rad_1h:J	18860.9	279202.425	1071799.5	float64
direct_rad:W	0.0	34.0875	530.15	float64
direct_rad_1h:J	0.0	129529.5	1895533.0	float64

effective_cloud_cover:p	85.375	99.975	100.0	float64
elevation:m	7.0	24.0	24.0	float64
fresh_snow_1h:cm	0.0	0.0	2.6	float64
fresh_snow_3h:cm	0.0	0.0	5.2	float64
fresh_snow_6h:cm	0.0	0.0	7.5	float64
hour	11.0	17.0	23.0	int64
is_day:idx	0.25	1.0	1.0	float64
is_estimated	1.0	1.0	1.0	int64
is_in_shadow:idx	1.0	1.0	1.0	float64
location				object
month	3.0	4.0	4.0	int64
msl_pressure:hPa	1011.625	1023.8125	1041.3501	float64
precip_5min:mm	0.0	0.0	0.2475	float64
precip_type_5min:idx	0.0	0.0	3.0	float64
pressure_100m:hPa	997.9	1009.875	1028.05	float64
pressure_50m:hPa	1004.1	1016.1625	1034.45	float64
rain_water:kgm2	0.0	0.0	0.175	float64
relative_humidity_1000hPa:p	73.1	82.075	98.0	float64
sample_weight	1.0	1.0	1.0	int64
sfc_pressure:hPa	1010.35	1022.5125	1040.8501	float64
snow_depth:cm	0.0	0.0	4.9	float64
snow_melt_10min:mm	0.0	0.0	0.14	float64
snow_water:kgm2	0.0	0.1	2.15	float64
sun_azimuth:d	179.52899	263.49875	347.37848	float64
sun_elevation:d	-0.79825	15.30325	41.13025	float64
super_cooled_liquid_water:kgm2	0.0	0.0	0.75	float64
t_1000hPa:K	275.175	277.525	285.1	float64
total_cloud_cover:p	96.65	100.0	100.0	float64
visibility:m	31311.025	40438.6635	66178.45	float64
weekday	3.0	5.0	6.0	int64
wind_speed_10m:ms	2.9	4.45	10.2	float64
wind_speed_u_10m:ms	0.3	2.9	9.95	float64
wind_speed_v_10m:ms	0.625	1.825	7.15	float64
y	0.0	142.906699	5172.64	float64
year	2023.0	2023.0	2023.0	int64

	missing_count	missing_ratio	raw_type	\
absolute_humidity_2m:gm3			float	
air_density_2m:kgm3			float	
ceiling_height_agl:m	1396	0.241064	float	
clear_sky_energy_1h:J	3	0.000518	float	
clear_sky_rad:W			float	
cloud_base_agl:m	857	0.147988	float	
dew_point_2m:K			float	
diffuse_rad:W			float	
diffuse_rad_1h:J	3	0.000518	float	
direct_rad:W			float	
direct_rad_1h:J	3	0.000518	float	

effective_cloud_cover:p			float
elevation:m			float
fresh_snow_1h:cm	3	0.000518	float
fresh_snow_3h:cm	3	0.000518	float
fresh_snow_6h:cm	3	0.000518	float
hour			int
is_day:idx			float
is_estimated			int
is_in_shadow:idx			float
location			object
month			int
msl_pressure:hPa			float
precip_5min:mm			float
precip_type_5min:idx			float
pressure_100m:hPa			float
pressure_50m:hPa			float
rain_water:kgm2			float
relative_humidity_1000hPa:p			float
sample_weight			int
sfc_pressure:hPa			float
snow_depth:cm			float
snow_melt_10min:mm			float
snow_water:kgm2			float
sun_azimuth:d			float
sun_elevation:d			float
super_cooled_liquid_water:kgm2			float
t_1000hPa:K			float
total_cloud_cover:p			float
visibility:m			float
weekday			int
wind_speed_10m:ms			float
wind_speed_u_10m:ms			float
wind_speed_v_10m:ms			float
y			float
year			int

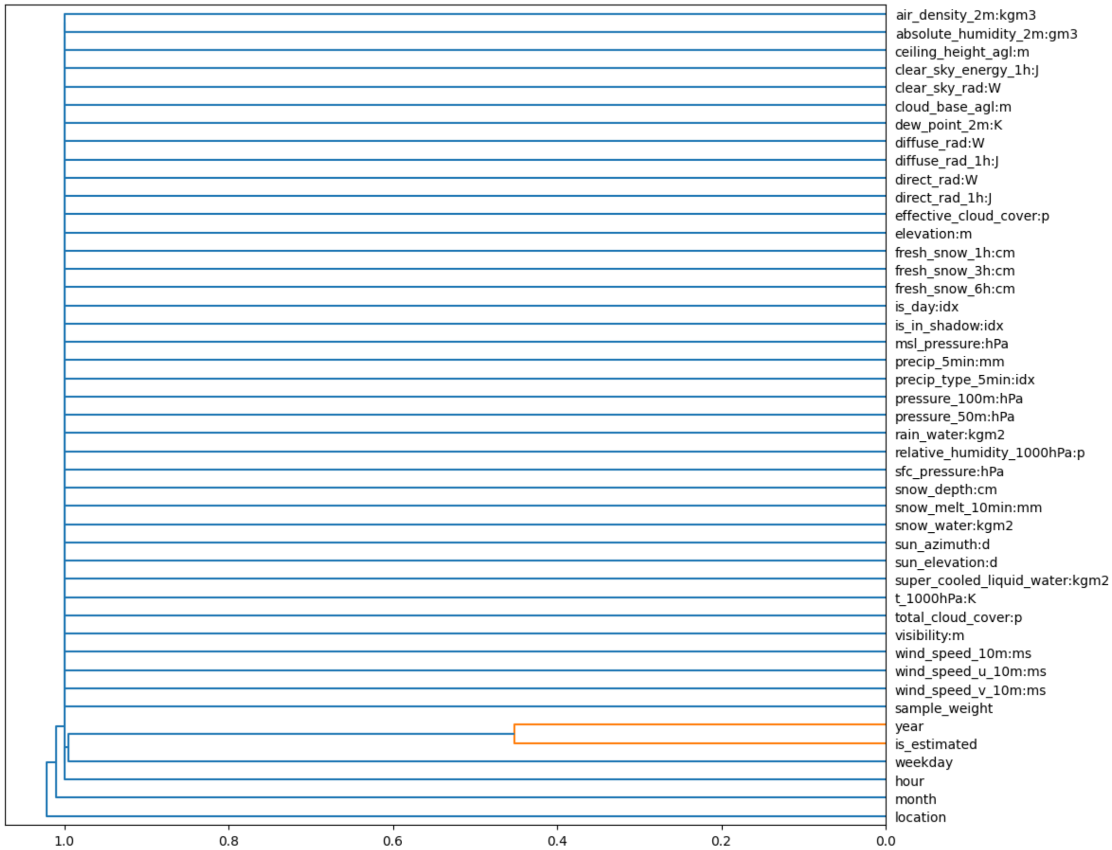
	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	

effective_cloud_cover:p	numeric
elevation:m	category
fresh_snow_1h:cm	numeric
fresh_snow_3h:cm	numeric
fresh_snow_6h:cm	numeric
hour	numeric
is_day:idx	category
is_estimated	category
is_in_shadow:idx	category
location	category
month	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sample_weight	category
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	numeric
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	numeric
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
y	numeric
year	category

Types warnings summary

	train_data	test_data	warnings
sample_weight	float	int	warning

1.0.1 Feature Distance

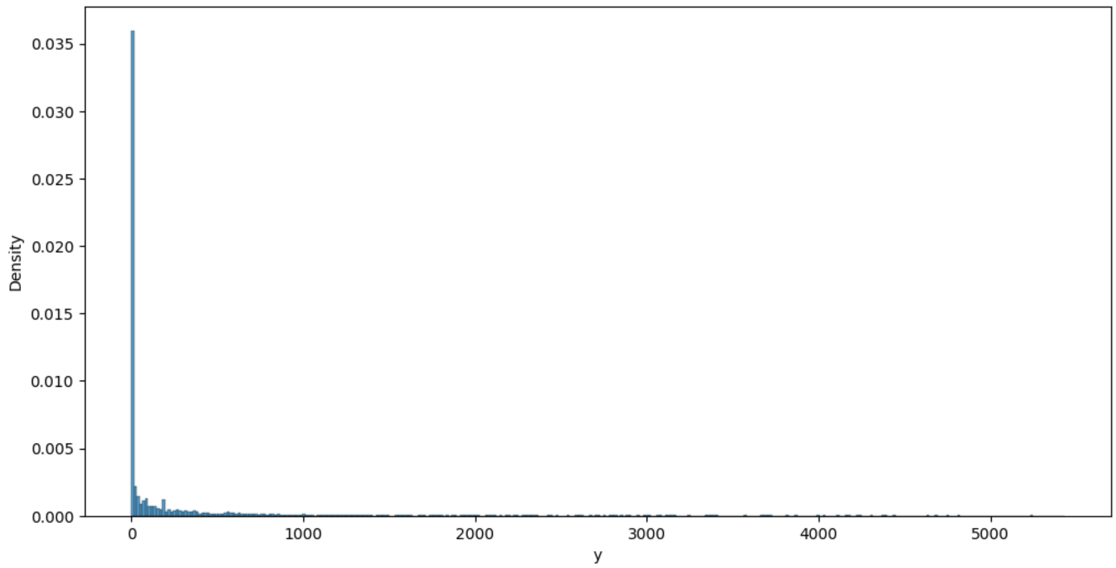


[6]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y")
```

1.1 Target variable analysis

```
   count       mean         std  min  25%  50%    75%      max   dtypes  \
y  10000  283.88153  748.627904  0.0  0.0  0.0  176.4  5428.72  float64

   unique missing_count missing_ratio raw_type special_types
y    2537                                 float
```

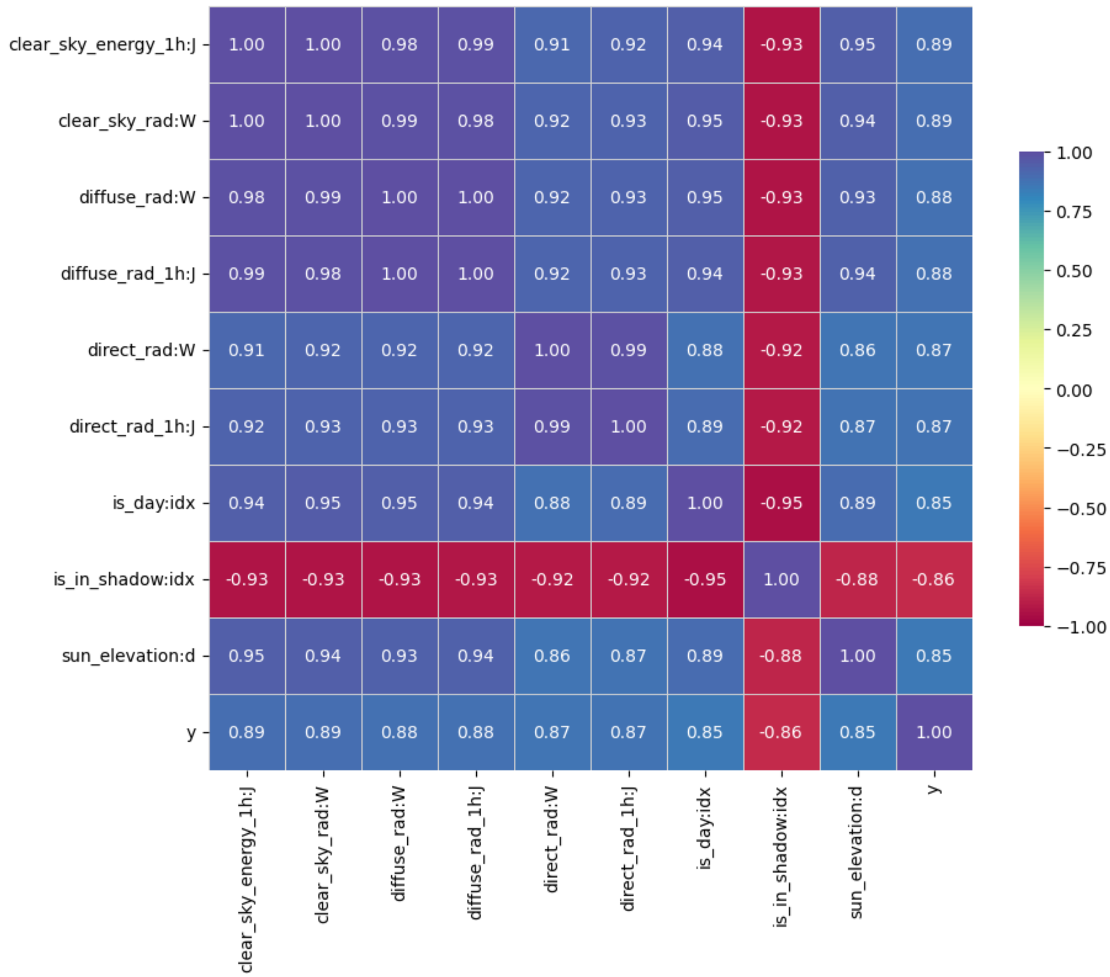


1.1.1 Distribution fits for target variable

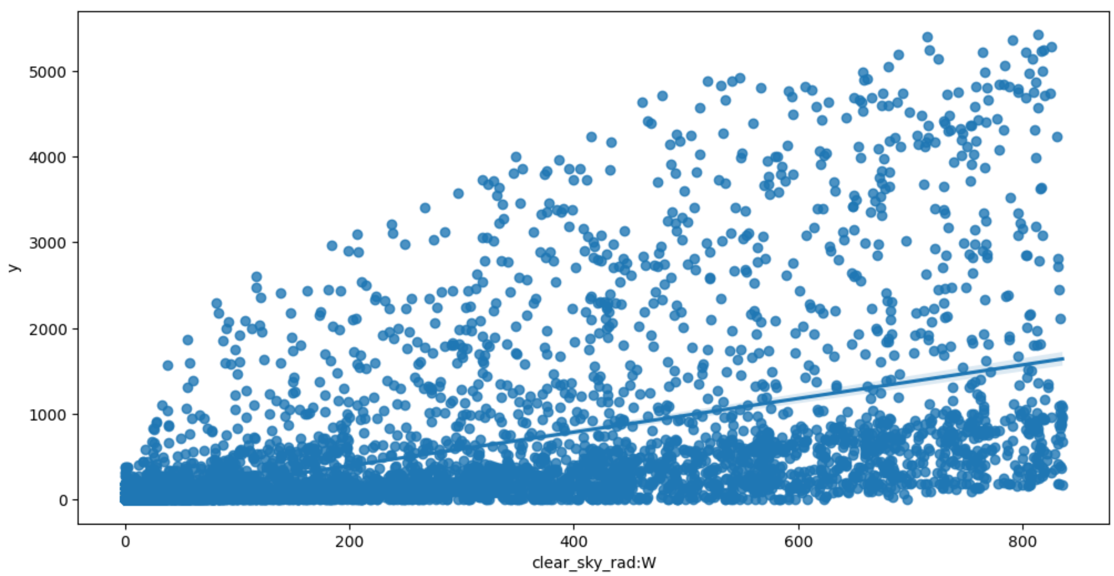
- none of the attempted distribution fits satisfy specified minimum p-value threshold: `0.01`

1.1.2 Target variable correlations

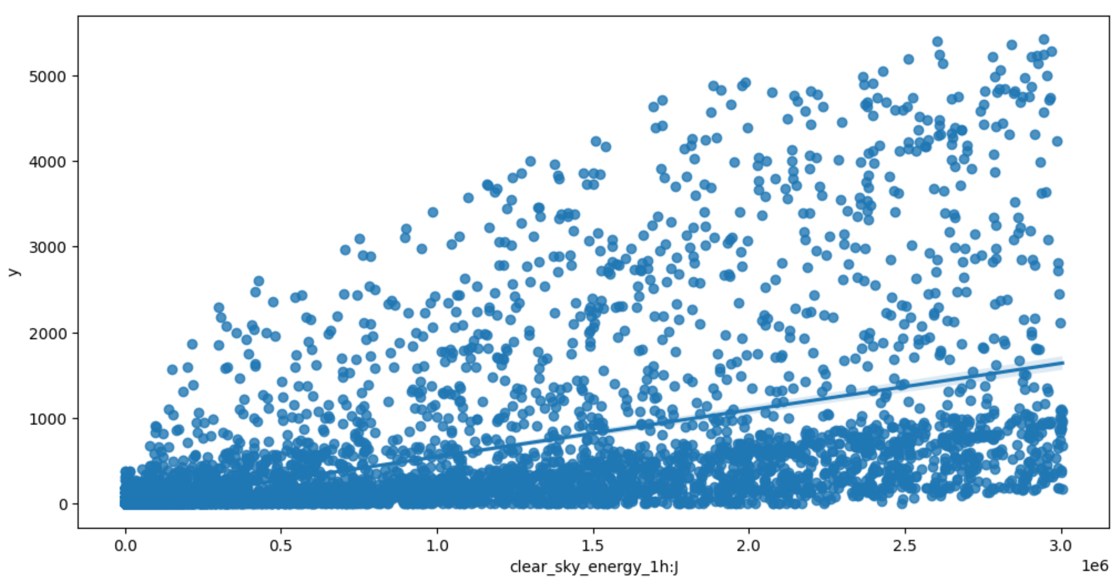
`train_data` - `spearman` correlation matrix; focus: absolute correlation for `y` >= `0.5` (sample size: 10000)



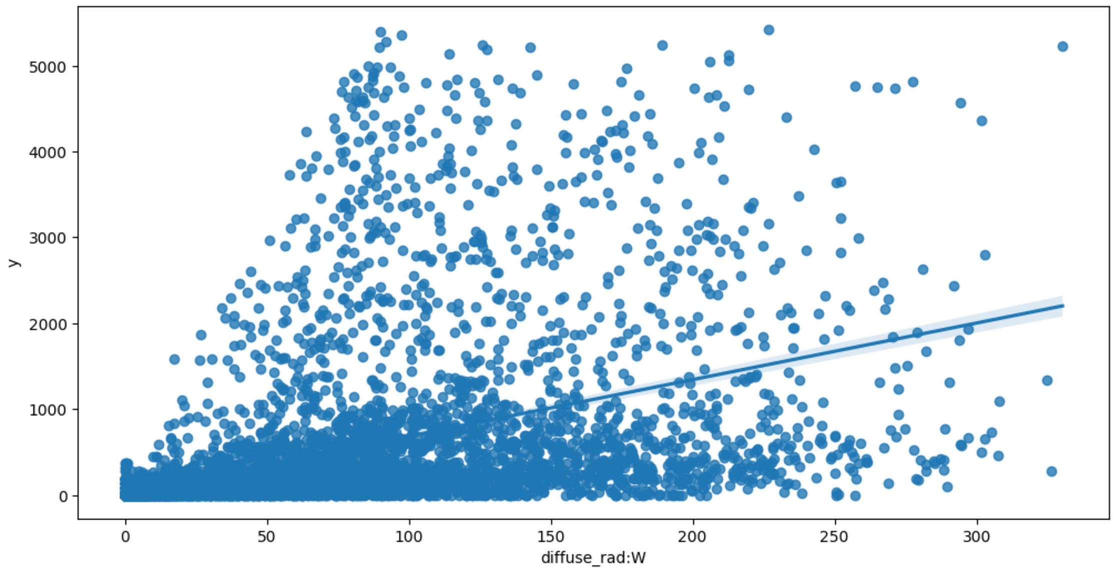
Feature interaction between `clear_sky_rad:W`/`y` in `train_data` (sample size: 10000)



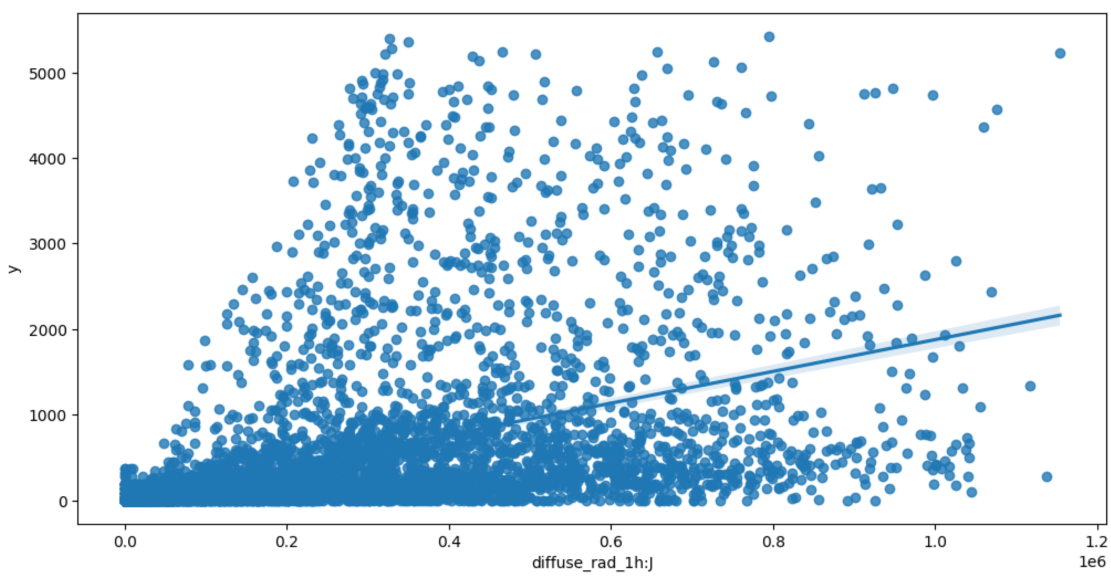
Feature interaction between `clear_sky_energy_1h:J/y` in `train_data` (sample size: 10000)



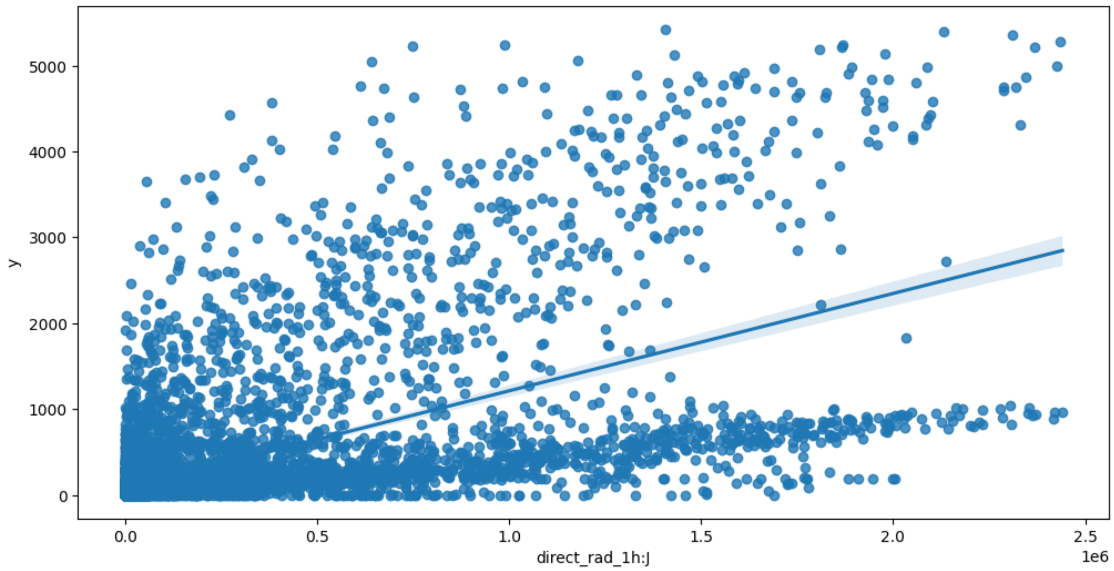
Feature interaction between `diffuse_rad:W/y` in `train_data` (sample size: 10000)



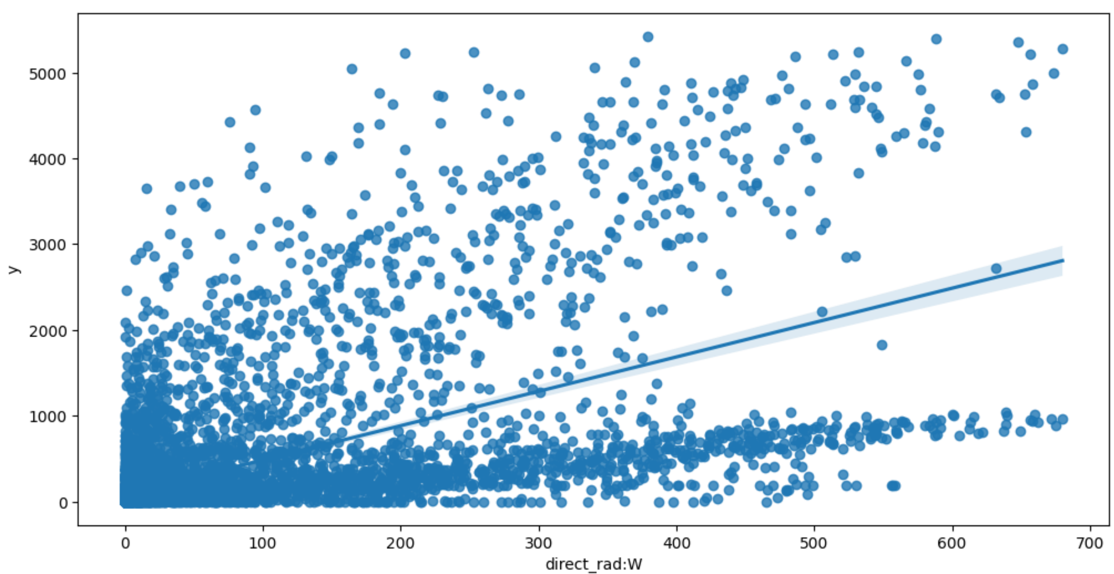
Feature interaction between `diffuse_rad_1h:J/y` in `train_data` (sample size: 10000)



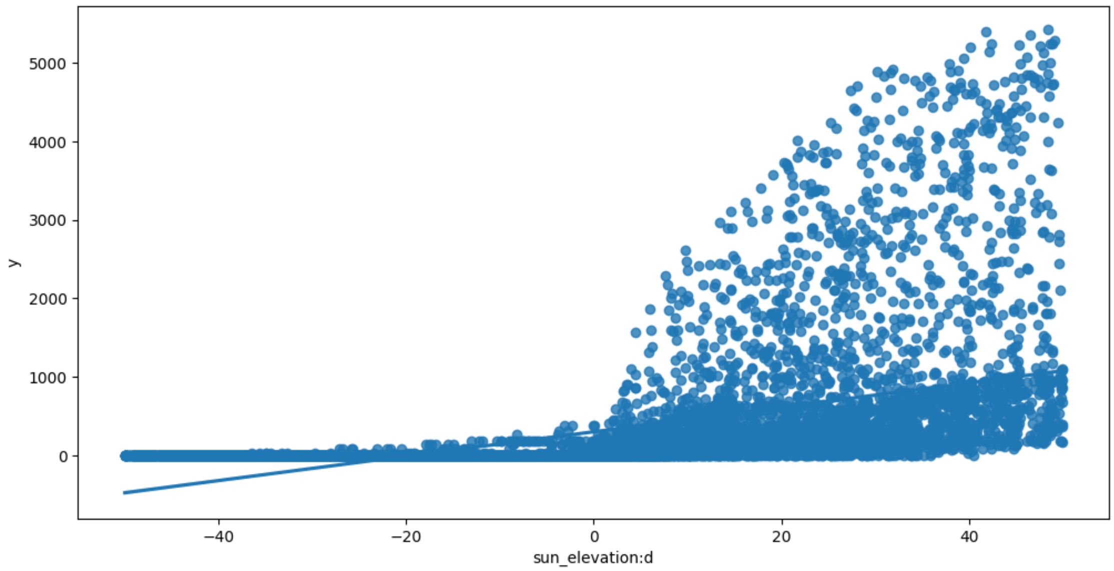
Feature interaction between `direct_rad_1h:J/y` in `train_data` (sample size: 10000)



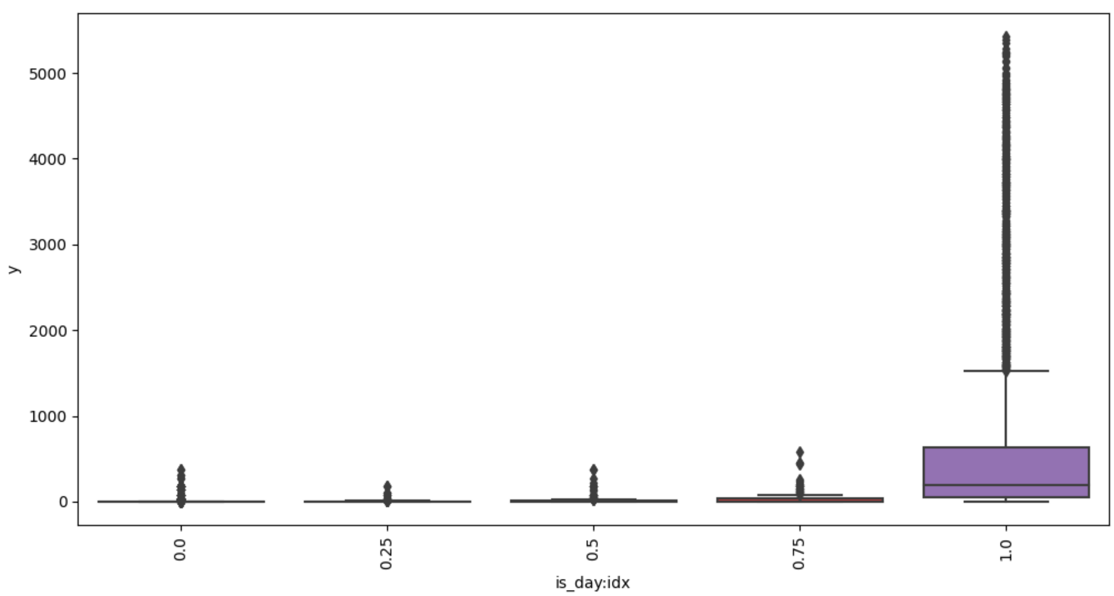
Feature interaction between `direct_rad:W`/y in `train_data` (sample size: 10000)



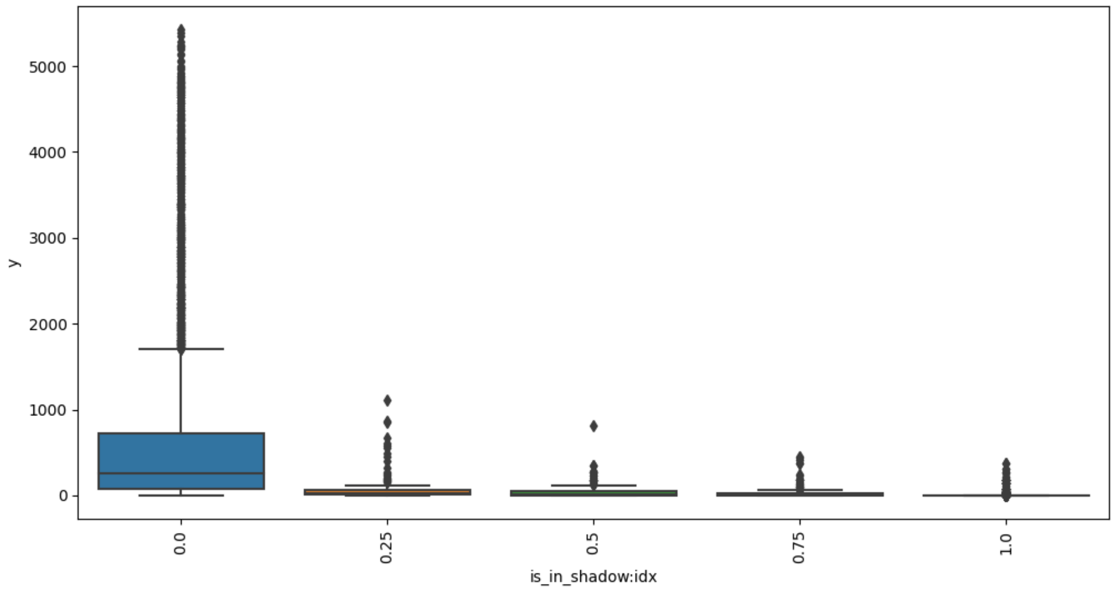
Feature interaction between `sun_elevation:d`/y in `train_data` (sample size: 10000)



Feature interaction between `is_day:idx`/`y` in `train_data` (sample size: 10000)



Feature interaction between `is_in_shadow:idx`/`y` in `train_data` (sample size: 10000)



2 Starting

[7]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
 ↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 91
Now creating submission number: 92
New filename: submission_92
```

[8]:
```
predictors = [None, None, None]
```

[ ]:

```python
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
↪train and tune data and test data
    print("Train data sample weight sum:", train_data[train_data["location"] ==␣
↪loc]["sample_weight"].sum())
    print("Train data number of rows:", train_data[train_data["location"] ==␣
↪loc].shape[0])
    if use_tune_data:
        print("Tune data sample weight sum:",␣
↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
        print("Tune data number of rows:", tuning_data[tuning_data["location"]␣
↪== loc].shape[0])
    if use_test_data:
        print("Test data sample weight sum:", test_data[test_data["location"]␣
↪== loc]["sample_weight"].sum())
        print("Test data number of rows:", test_data[test_data["location"] ==␣
↪loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        sample_weight=sample_weight,
        weight_evaluation=weight_evaluation,
        groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc],
        time_limit=time_limit,
        presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        tuning_data=tuning_data[tuning_data["location"] == loc] if␣
↪use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])
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    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
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Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 3600s
AutoGluon will save models to "AutogluonModels/submission_92_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   258.31 GB / 315.93 GB (81.8%)
Train Data Rows:    34085
Train Data Columns: 45
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 630.59471,
1165.90242)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    132186.64 MB
        Train Data (Original)  Memory Usage: 13.97 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…

Training model for location A…
Train data sample weight sum: 34085.0
Train data number of rows: 34085
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        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['sample_weight', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 38 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  5 | ['is_estimated', 'hour', 'year', 'month',
'weekday']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 37 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'year', 'month', 'weekday']
                ('int', ['bool']) :  2 | ['elevation:m', 'is_estimated']
        0.2s = Fit runtime
        43 features in original data used to generate 43 features in processed
data.
        Train Data (Processed) Memory Usage: 11.25 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.19s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
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        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 2399.27s of
the 3599.81s of remaining time.
        -227.8215        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.39s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 2398.74s of
the 3599.27s of remaining time.
        -228.9711        = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        0.4s     = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 2398.25s of the
3598.78s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -145.8233        = Validation score   (-mean_absolute_error)
        39.85s   = Training   runtime
        21.83s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 2349.75s of the
3550.29s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -158.5945        = Validation score   (-mean_absolute_error)
        45.93s   = Training   runtime
        19.27s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 2299.82s of
the 3500.36s of remaining time.
        -176.1868        = Validation score   (-mean_absolute_error)
        11.06s   = Training   runtime
        1.43s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2286.7s of the
3487.23s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -166.0487        = Validation score   (-mean_absolute_error)
        210.04s  = Training   runtime
        0.11s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 2075.6s of the
3276.14s of remaining time.
        -176.5081        = Validation score   (-mean_absolute_error)
        2.31s    = Training   runtime
        1.41s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2071.23s of
the 3271.77s of remaining time.
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        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -180.6454        = Validation score   (-mean_absolute_error)
        41.99s   = Training   runtime
        0.65s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2028.12s of the
3228.65s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -169.4328        = Validation score   (-mean_absolute_error)
        92.72s   = Training   runtime
        7.74s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1932.11s of
the 3132.65s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -163.8387        = Validation score   (-mean_absolute_error)
        170.15s  = Training   runtime
        0.38s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1760.66s of the
2961.19s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -154.9924        = Validation score   (-mean_absolute_error)
        141.86s  = Training   runtime
        28.16s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1610.37s of the
2810.9s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -142.0083        = Validation score   (-mean_absolute_error)
        78.59s   = Training   runtime
        39.19s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1568.06s of the
2768.59s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -154.0039        = Validation score   (-mean_absolute_error)
        92.14s   = Training   runtime
        36.68s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1517.65s of the
2718.18s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -161.6323        = Validation score   (-mean_absolute_error)
        418.57s  = Training   runtime
        0.22s    = Validation runtime
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Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1307.92s of
the 2508.45s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -176.7242        = Validation score   (-mean_absolute_error)
        84.77s   = Training   runtime
        1.33s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1263.71s of the
2464.24s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -163.9825        = Validation score   (-mean_absolute_error)
        197.63s  = Training   runtime
        23.57s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1155.57s of
the 2356.11s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -159.5792        = Validation score   (-mean_absolute_error)
        281.6s   = Training   runtime
        0.77s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1042.93s of the
2243.47s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -152.4076        = Validation score   (-mean_absolute_error)
        284.39s  = Training   runtime
        54.25s   = Validation runtime
Completed 2/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
2093.15s of remaining time.
        -141.2395        = Validation score   (-mean_absolute_error)
        0.72s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 2092.42s of the
2092.41s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -144.692         = Validation score   (-mean_absolute_error)
        4.0s     = Training   runtime
        0.24s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 2087.13s of the
2087.11s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.7059        = Validation score   (-mean_absolute_error)
        2.15s    = Training   runtime
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        0.09s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 2083.66s of
the 2083.65s of remaining time.
        -139.0156        = Validation score   (-mean_absolute_error)
        16.64s   = Training   runtime
        1.45s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 2064.76s of the
2064.74s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.7793        = Validation score   (-mean_absolute_error)
        6.42s    = Training   runtime
        0.04s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L2 … Training model for up to 2057.01s of the
2057.0s of remaining time.
        -138.8443        = Validation score   (-mean_absolute_error)
        2.92s    = Training   runtime
        1.45s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 2051.98s of
the 2051.96s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.8624        = Validation score   (-mean_absolute_error)
        42.32s   = Training   runtime
        0.67s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 2008.33s of the
2008.32s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.7653        = Validation score   (-mean_absolute_error)
        3.13s    = Training   runtime
        0.13s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 2003.83s of
the 2003.82s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -142.8088        = Validation score   (-mean_absolute_error)
        69.76s   = Training   runtime
        0.5s     = Validation runtime
Fitting model: LightGBMLarge_BAG_L2 … Training model for up to 1932.73s of the
1932.71s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.997         = Validation score   (-mean_absolute_error)
        7.57s    = Training   runtime
        0.18s    = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 1923.89s of the
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1923.88s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -143.8685        = Validation score   (-mean_absolute_error)
        8.09s    = Training   runtime
        0.45s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 1918.51s of the
1918.49s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.309         = Validation score   (-mean_absolute_error)
        4.41s    = Training   runtime
        0.17s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 1914.92s of the
1914.9s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.1452        = Validation score   (-mean_absolute_error)
        14.67s   = Training   runtime
        0.08s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 1905.42s of
the 1905.41s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.6635        = Validation score   (-mean_absolute_error)
        85.09s   = Training   runtime
        1.37s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 1861.39s of the
1861.38s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.9937        = Validation score   (-mean_absolute_error)
        6.18s    = Training   runtime
        0.27s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 1856.95s of
the 1856.93s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -141.4436        = Validation score   (-mean_absolute_error)
        144.75s  = Training   runtime
        1.04s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L2 … Training model for up to 1780.59s of the
1780.58s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.0472        = Validation score   (-mean_absolute_error)
        14.63s   = Training   runtime
        0.35s    = Validation runtime
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Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 1772.29s of the
1772.28s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -143.5864        = Validation score   (-mean_absolute_error)
        12.27s   = Training   runtime
        0.68s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 1766.82s of the
1766.81s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.1859        = Validation score   (-mean_absolute_error)
        6.61s    = Training   runtime
        0.26s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 1763.32s of the
1763.31s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.1084        = Validation score   (-mean_absolute_error)
        20.49s   = Training   runtime
        0.13s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 1756.32s of
the 1756.31s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.1848        = Validation score   (-mean_absolute_error)
        128.39s  = Training   runtime
        2.03s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 1711.71s of the
1711.69s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.6693        = Validation score   (-mean_absolute_error)
        9.43s    = Training   runtime
        0.39s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 1707.07s of
the 1707.05s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.9709        = Validation score   (-mean_absolute_error)
        207.49s  = Training   runtime
        1.6s     = Validation runtime
Fitting model: LightGBMLarge_BAG_L2 … Training model for up to 1642.94s of the
1642.93s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.5972        = Validation score   (-mean_absolute_error)
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        22.08s   = Training   runtime
        0.54s    = Validation runtime
Repeating k-fold bagging: 4/20
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 1634.22s of the
1634.2s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -143.3924        = Validation score   (-mean_absolute_error)
        16.25s   = Training   runtime
        0.92s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 1628.9s of the
1628.89s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.1448        = Validation score   (-mean_absolute_error)
        8.92s    = Training   runtime
        0.34s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 1625.39s of the
1625.38s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.0229        = Validation score   (-mean_absolute_error)
        26.33s   = Training   runtime
        0.17s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 1618.17s of
the 1618.16s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -137.91  = Validation score   (-mean_absolute_error)
        170.99s  = Training   runtime
        2.71s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 1574.31s of the
1574.3s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.5664        = Validation score   (-mean_absolute_error)
        12.6s    = Training   runtime
        0.53s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 1569.87s of
the 1569.85s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.7158        = Validation score   (-mean_absolute_error)
        279.93s  = Training   runtime
        2.13s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L2 … Training model for up to 1496.09s of the
1496.08s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
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ParallelLocalFoldFittingStrategy
        -139.502         = Validation score   (-mean_absolute_error)
        29.7s    = Training   runtime
        0.73s    = Validation runtime
Repeating k-fold bagging: 5/20
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 1487.16s of the
1487.15s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -143.2448        = Validation score   (-mean_absolute_error)
        20.88s   = Training   runtime
        1.17s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 1481.14s of the
1481.13s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.011         = Validation score   (-mean_absolute_error)
        11.23s   = Training   runtime
        0.43s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 1477.61s of the
1477.59s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.9292        = Validation score   (-mean_absolute_error)
        35.63s   = Training   runtime
        0.22s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 1466.99s of
the 1466.98s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -137.7668        = Validation score   (-mean_absolute_error)
        214.11s  = Training   runtime
        3.35s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 1422.62s of the
1422.61s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.393         = Validation score   (-mean_absolute_error)
        15.79s   = Training   runtime
        0.66s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 1418.08s of
the 1418.06s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -140.6117        = Validation score   (-mean_absolute_error)
        347.11s  = Training   runtime
        2.69s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L2 … Training model for up to 1349.59s of the
```

```
1349.58s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.3613        = Validation score   (-mean_absolute_error)
        37.03s   = Training   runtime
        0.92s    = Validation runtime
Repeating k-fold bagging: 6/20
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 1340.97s of the
1340.96s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -143.1426        = Validation score   (-mean_absolute_error)
        25.61s   = Training   runtime
        1.39s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 1334.82s of the
1334.81s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.9207        = Validation score   (-mean_absolute_error)
        13.58s   = Training   runtime
        0.52s    = Validation runtime
Fitting model: CatBoost_BAG_L2 … Training model for up to 1331.28s of the
1331.27s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -139.9517        = Validation score   (-mean_absolute_error)
        42.21s   = Training   runtime
        0.26s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L2 … Training model for up to 1323.47s of
the 1323.45s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -137.6445        = Validation score   (-mean_absolute_error)
        257.21s  = Training   runtime
        4.05s    = Validation runtime
Fitting model: XGBoost_BAG_L2 … Training model for up to 1279.07s of the
1279.05s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -138.317         = Validation score   (-mean_absolute_error)
        19.24s   = Training   runtime
        0.8s     = Validation runtime
Fitting model: NeuralNetTorch_BAG_L2 … Training model for up to 1274.35s of
the 1274.34s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

[ ]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
```

[ ]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
```

3 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])

#test_data_merged
```

[ ]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    past_pred = predictors[i].
↪predict(train_data_with_dates[train_data_with_dates["location"] == loc])
```

```
    train_data_with_dates.loc[train_data_with_dates["location"] == loc,␣
 ↪"prediction"] = past_pred
```

[ ]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='prediction', ax=ax, label="past predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```

[ ]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
# Save the submission DataFrame to submissions folder, create new name based on␣
 ↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
 ↪index=False)
print("jall1a")
```

[ ]:
```
# save this running notebook
from IPython.display import display, Javascript
import time

# hei123

display(Javascript("IPython.notebook.save_checkpoint();"))

time.sleep(3)
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
```

```
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

[ ]:
```
# feature importance
location="A"
split_time = pd.Timestamp("2022-10-28 22:00:00")
estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
estimated = estimated[estimated["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=estimated,␣
↪time_limit=60*10)
```

[ ]:
```
# feature importance
observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
observed = observed[observed["location"] == location]
predictors[0].feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

[ ]:
```
display(Javascript("IPython.notebook.save_checkpoint();"))
time.sleep(3)

subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename
```

```python
# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push', 'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream', 'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```